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MODELING THE FORMATION OF EXPECTATIONS:
THE HISTORY OF ENERGY DEMAND FORECASTS

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ABSTRACT

Since 1973 forecasts of future energy consumption in the United States have fallen dramatically. Forecasts of consumption in 1985 made as recently as 1974 were too high by nearly a factor of two. Forecasts for consumption in 2000 have fallen by a similar ratio over the same period. This paper tests the ability of adaptive expectations and univariate trend extrapolation to explain the history of energy demand forecasts. A behavioral model of the trend estimation and forecasting process is developed. Energy demand is forecast by extrapolation of the expected growth rate of consumption. The expected growth rate is determined by the past rate of growth of actual energy consumption. The model explicitly considers delays in the measurement of energy consumption and in individual and organizational response to changes in the apparent trend. The model is shown to fit the forecast data well for three different forecast horizons. Univariate trend extrapolation and adaptive expectations thus account well for significant evolution of energy demand forecasts during a major period of change in energy consumption. The results are reconciled with the fact that many of the forecasts in the sample were based on complex models and were plainly not simple extrapolations, and implications for behavioral modeling of expectation formation are discussed.

MODELING THE FORMATION OF EXPECTATIONS:
THE HISTORY OF ENERGY DEMAND FORECASTS

Since 1973 estimates of future energy consumption in the United States have fallen dramatically (exhibit 1). Before the first oil crisis forecasters expected energy consumption to grow as it had been during the 1950s and '60s. Forecasts made as recently as 1974 projected consumption in 1985 to be near 130 quadrillion BTUs (quads). Actual energy consumption in 1985 was less than 74 quads. In like fashion, forecasts of consumption in 2000 have fallen by nearly a factor of two since 1973. Higher energy prices coupled with lower rates of economic growth are usually cited as causes of the lower forecasts. Nevertheless, the large errors and seemingly reactive nature of the forecasts lead to questions about the nature and rationality of the forecasting methods used.

The evolution of the forecasts also raises questions about how expectation formation should be portrayed in energy, macroeconomic and other policy-oriented models. Behavioral simulation models are one important class of such models.¹ Behavioral simulation models usually portray expectations as adaptive learning processes. Growth expectations are often modeled as a distributed lag of past rates of growth, and forecasts are simple extrapolations. Trend extrapolation, however, seems naive to many observers, who point out that energy demand forecasts, for example, are often the result of extensive studies involving detailed, multidisciplinary analysis, analysis which takes a wide range of factors into account.² How can adaptive expectations and trend extrapolation be used to proxy such complex and subtle decisionmaking?

The model described here tests the ability of adaptive expectations and trend extrapolation to explain the history of energy demand forecasts. Energy demand is forecast by an exponential extrapolation of the expected growth rate of energy consumption. The expected rate of consumption growth is determined by the past rate of growth of actual energy consumption. Delays in measuring and reacting to changes in energy consumption are explicitly represented.

The model is used to generate forecasts for 1980, 1985, and 2000 using the historical values of energy consumption from 1947 onward. The simulated forecasts are shown to fit the actual forecasts quite well. Univariate trend extrapolation thus accounts for significant evolution of energy demand forecasts over a period of more than a decade during which energy consumption underwent major shifts. This is reconciled with the fact that many forecasts are based on complex models and are plainly not univariate trend extrapolations. Finally, implications for use of extrapolative expectations in behavioral simulation models are discussed.

The Model

Expectations are usually modeled in behavioral simulation as adaptive learning processes (e.g. Holt et al. 1960, Forrester 1961, Cyert and March 1963, Mass 1975, Lyneis 1980, Meadows 1970, Low 1974, Sterman and Richardson 1985). Adaptive expectations are common in economic models as well, for example Irving Fisher's (1930) theory of interest rates, Nerlove's (1958) cobweb model (Arrow and Nerlove 1958), Friedman's (1957) permanent income hypothesis, Ando and Modigliani's (1963) lifecycle hypothesis of saving, Eckstein's (1981) theory of "core inflation" as well as a host of macroeconometric and other forecasting models.³ For example, a firm's expectation of the order rate for its product is often assumed to

adjust over time to the actual order stream. Often, the adjustment is assumed to be first-order information smoothing, though more complex patterns of adjustment may be chosen (e.g. Weymar 1968). Adaptive expectations are often a good representation of the actual forecasting or expectation formation process in organizations and single exponential smoothing has been shown (in the M-competition) to outperform many other forecasting methods over longer time horizons (Makridakis et al. 1982, Makridakis et al. 1984, Carbone and Makridakis 1986). However, sometimes expectations respond not just to the past history of the variable but to its past growth rate as well. For example, the past values and past trend in orders may be used to estimate the likely future order rate.

The formation of growth expectations in behavioral simulation and system dynamics is often modeled with the TREND function (Richmond 1977, Richardson and Pugh 1981). The TREND function is a set of differential equations which represent the formation of expectations about the current rate of growth in a given variable. TREND is not just a clever way to calculate the rate of growth of a variable, however. As the input to decision rules in models, TREND represents a behavioral theory of how people form expectations, and takes into account the time required for people to collect and analyze data, and to react to changes in the growth rate.

The causal structure of the TREND function is given in exhibit 2. The TREND function can be thought of as an information processing scheme which takes as input a variable (including its past values) and produces as output a judgement of the current trend in the input variable:

$$\text{TREND}_t = f(\text{INPUT}_T) \quad T: (t_o, t). \quad (1)$$

The expected growth rate TREND is a state variable whose derivative is:

$$(d/dt)TREND_t = (ITREND_t - TREND_t) / TPT \quad (2)$$

where

TREND = expected trend in input variable (1/years)
 ITREND = indicated trend in input variable (1/years)
 TPT = time to perceive trend (years)
 INPUT = input variable (input units).

The value of TREND is the expected rate of change in the input variable, expressed as a fraction of the input variable per time unit. It is assumed that the trend perceived and acted upon by decisionmakers adjusts adaptively to the trend indicated by the most recently available data, given by ITREND. First-order information smoothing is assumed.

The lag in the adjustment of the perceived trend to the indicated trend represents the time required for a change in the indicated trend to be recognized, accepted, and acted upon by decisionmakers. The delay in the acceptance of a new trend as an operational input is often significant. The adjustment lag depends not only on the time required for individual decisionmakers to recognize the change, but on organizational inertia: a new trend may have to become part of the "conventional wisdom" before some are willing to act.

$$ITREND_t = [(PPC_t - RC_t) / RC_t] / THRC \quad (3)$$

where

ITREND = indicated trend (1/years)
 PPC = perceived present condition (input units)
 RC = reference condition (input units)
 THRC = time horizon for reference condition (years).

The indicated trend is given by the difference between the perceived present condition of the input and its average value over some historical horizon (the reference condition), expressed as a fraction of the reference condition and annualized by the time horizon between the perceived present condition and the reference condition.

$$(d/dt)PPC_t = (INPUT_t - PPC_t)/TPPC \quad (4)$$

where

PPC = perceived present condition of input (input units)
 INPUT = input to trend function (input units)
 TPPC = time to perceive present condition (years).

The indicated trend depends not on the true value of the input variable but on the perceived present condition, which is an exponential smooth of the raw input. The smoothing represents two factors. First, assessing current status takes time. There is an inevitable delay in measuring the input variable and disseminating information about its recent values. In the case of corporate and aggregate economic data, the data collection and reporting lag may range from several weeks to a year. In the case of demographic, resource, or environmental data, the delays may be even longer. Second, even if the raw data were available immediately, smoothing is desirable to filter out the high frequency noise in the raw values that does not reflect the underlying trend. Such noise arises from both the processes themselves, from measurement error, and from subsequent revisions in the reported data.

The reference condition RC is also a state variable:

$$(d/dt)RC_t = (PPC_t - RC_t)/THRC. \quad (5)$$

The reference condition of the input reflects the value of the input at some time in the past. The time horizon for the reference condition THRC determines the relevant historical period considered in the forecasting process. Equivalently, $1/THRC$ is the rate at which old information is discounted. The reference condition is computed by smoothing the perceived present condition. Note that the reference condition is based on the perceived present condition rather than the input variable itself. Raw values of the input are not actually available to decisionmakers--in most

cases, only averaged data, reported after a significant collection and reporting delay, are available.

The judgement of the trend in a variable is often subjective, and strongly conditioned by experience. Thus, the time horizon for establishing the reference condition may reflect the memory and experience of individual decisionmakers. For example, managers whose professional experience was conditioned by the high-growth decades of the 1950s and 60s may continue to forecast high growth despite the low actual growth rates of the 1970s and 80s. Their judgement may reflect a belief that the past "few years" are an aberration and the economy will soon resume the growth rate that characterized the past. In such a case, perceived trends may change only as fast as management turns over and is replaced.

The TREND function provides a behavioral representation of trend estimation. The formulation assumes expectations about the underlying trend in a variable are based upon the historical rate of growth in the variable itself. Further, people are assumed to react slowly to changes in the trend, adapting over time to new conditions as new information becomes available, as they come to believe that a new growth rate is lasting enough to warrant its use in decisions, and as the organization adjusts to the new conditions. The model takes the time required to collect, analyze, and report the value of the input variable into account. It permits the modeler to specify the historical time horizon relevant to the determination of the trend. The model is intendedly quite simple and does not include the possibility that the parameters may vary endogenously as conditions change. For example the parameters may plausibly be argued to vary with the dispersion of the input series. While changes in the forecasting process can be modeled (e.g. Caskey 1985), the purpose of the

analysis below is to examine the extent to which the simpler fixed parameter model can explain the major shifts in energy demand forecasts.

Behavior of the TREND function

To be a reasonable model of growth expectation formation, TREND should produce, in the steady state, an accurate estimate of the growth rate in the input variable. That is, if

$$\text{INPUT}_t = \text{INPUT}_{t_0} * \exp(g*(t-t_0)) \quad (6)$$

then

$$\lim_{t \rightarrow \infty} \text{TREND}_t = g.$$

The proof relies on the fact that the steady-state response of a first-order exponential smoothing process to exponential growth is exponential growth at the same rate as the input. But in the steady state, the smoothed variable lags behind the input by a constant fraction of the smoothed value. To prove this fact, one must solve the differential equation for a first-order smoothing process:

$$(dy/dt) = y' = (x-y)/AT \quad (7)$$

where $x = x_0 \exp(g(t-t_0))$, x_0 and t_0 are initial values, g = growth rate and AT = the adjustment time of the smoothing process. The solution of equation (7) can be found in any introductory differential equations text. The result of interest is that in the steady state, the fractional rate of change in y ,

$$y'/y = g. \quad (8)$$

But since $y' = (x-y)/AT$, the fractional steady state error between x and y is

$$(x-y)/y = gAT \quad (9)$$

or

$$y = x/(1+gAT). \quad (9')$$

The steady state error is proportional to both the growth rate of the input and the average lag between input and output. The solution can be verified by substitution in the differential equation.

In the TREND function, PPC is a smooth of INPUT, so in the steady state, PPC will be growing exponentially at rate g . Since RC is a smooth of PPC, it will also be growing at the fractional rate of g per time unit. Therefore, $g = RC' / RC$. But

$$RC' = (PPC - RC) / THRC \quad (10)$$

so

$$g = [(PPC - RC) / THRC] / RC = ITREND. \quad (11)$$

Since TREND is a smooth of ITREND, $TREND = ITREND = g$ in the steady state. Thus, in the steady state, TREND yields an unbiased estimate of the exponential growth rate in the input variable.

During transients, of course, TREND will differ from the true growth rate of the input. To illustrate the transient response of the TREND function, exhibit 3 shows the adjustment of the expected trend to an exponentially growing input for various values of the three parameters TPT, TPPC, and THRC. In the example the input grows at 5 percent/year, starting from a stationary equilibrium. The true growth rate thus follows a step input from 0 to 5 percent. In all cases the response of TREND is s-shaped. The expected trend smoothly approaches the true trend from below, without overshoot. The parameters TPT, TPPC, and THRC control the mean and shape of the distributed lag response of TREND to a change in the input's growth rate.⁴

Modeling Energy Demand Forecasts

The TREND function provides the expectation or judgement of the growth rate in the input variable at the current moment in time. To produce a forecast

of the input's value at some point in the future one must assume some degree of persistence. For example, one might assume that the current fractional growth rate in the input will continue throughout the forecast horizon. Alternatively, one might assume that the rate gradually approaches some more fundamental reference, that growth will be linear rather than exponential, or that the variable itself asymptotically approaches some limit.

The forecasting process used here assumes continued exponential growth in primary energy consumption at the currently perceived rate:

$$FC(FY)_t = PPC_t * (1 + TREND_t * TPPC) * \exp[TREND_t * (FY - t)] \quad (12)$$

where

FC(FY) = Forecast Consumption in Forecast Year (Quads/year)
 FY = Forecast Year (year)
 PPC = Perceived Present Condition (consumption) (Quads/year)
 TREND = Expected Trend in Consumption (1/years)
 TPPC = Time to Perceive Present Condition (years).

Note that equation (12) assumes forecasters recognize that it takes time to perceive the input and also that the input will have grown during the interval. They are assumed to compensate by adjusting consumption for growth at the currently perceived rate between the time it was measured and the present.

Note also that equation (12) produces an accurate forecast of the input when the input is exponential growth. Assuming INPUT grows at rate g ,

$$INPUT_{FY} = INPUT_t * \exp(g * (FY - t)). \quad (13)$$

By equation (9'),

$$INPUT_t = PPC_t * (1 + g * TPPC). \quad (14)$$

Substituting equation (14) for INPUT,

$$INPUT_{FY} = PPC_t * (1 + g * TPPC) * \exp(g * (FY - t)). \quad (15)$$

Since $TREND = g$ in the steady state, the right hand side of (15) is precisely the expression for $FC(FY)_t$.⁵

Parameter Estimation

The proposed model involves only three parameters: TPT, TPPC, and THRC. In addition the initial growth rate of energy consumption must be specified. In all cases, the simulations begin in 1947 with an assumed initial growth rate of 2%/year.⁶ Given the parameter values reported below, the simulated forecasts are virtually independent of the initial growth rate by the late 1950s, when the actual forecast data begin.

Note that all parameters yield the same result in the steady state. Thus to estimate the model the actual growth rate of the input variable must vary significantly. Fortunately, the energy consumption and forecast data span a period which includes major changes in patterns of energy use, first accelerating up to 1973 and rapidly decelerating thereafter.

The model is nonlinear, and the parameters were estimated with a multivariate hillclimbing program.⁷ The mean absolute error (MAE) between the actual and simulated forecasts was chosen as the criterion of fit to be minimized in estimating the parameters:

$$MAE=MAE(TPT,TPPC,THRC)=(1/N) \sum_{t=1947}^{1985} \sum_i |HFC(FY)_{t,i} - FC(FY)_t| \quad (16)$$

where

N = total forecasts available for forecast horizon FY
 HFC(FY)= historical forecasts for forecast horizon FY (quads/year)
 FC(FY) = simulated forecasts for forecast horizon FY (quads/year)
 i = index of forecasts HFC(FY) made in year t

To guard against the possibility of finding only local minima, the hillclimbing procedure was run from a variety of initial parameter values.

Exhibit 4 presents the optimal parameter estimates for each forecast horizon. Note that because there are often several different forecasts for each year, the minimum possible error is not zero. The MAE is compared

against the mean absolute deviation of the historical forecasts. The mean absolute deviation (MAD) is computed exactly as in equation 16 but replacing the simulated forecast with the median of the historical forecasts for each year. Since the median minimizes absolute deviation, the MAD of the historical forecasts represents the best possible fit and is the lower bound on the MAEs reported in the exhibit.

The optimal parameters for 1980 and 1985 produce MAEs quite close to the lower bound. As a percentage of the mean historical forecasts, the increase in MAE over the MAD is just 5 and 2 percent for 1980 and 1985, respectively. Exhibits 5, 6 and 7 compare the simulated and actual forecasts for each forecast horizon, using the optimal parameters. The simulated forecasts for 1980 are somewhat low before 1965 but are a good fit after that date. Likewise the simulated forecasts for 1985 are an excellent fit.

However, exhibits 4 and 7 show the optimal parameters for the year 2000 forecasts, particularly TPT and TPPC, to be implausibly short. The short delays in assessing current consumption and reacting to changes in the growth rate mean the simulated forecast is far too volatile, swinging wildly in response to business cycle fluctuations in energy consumption. Further, the simulated forecast is biased upward, reaching a peak of over 250 quads in 1969. Setting the parameters to the optimal values for 1985 results in the forecasts shown in exhibit 8. Here the extreme volatility of the forecasts is reduced, but the forecasts are consistently too high, reaching a peak of 225 quads in 1971 and producing an MAE of 33 quads, double the mean absolute deviation of the historical forecasts.

The overestimation of the year 2000 forecasts is curious in light of the fact that the 1985 forecasts are unbiased. The forecasting procedure

in equation 12 presumes a continuation of exponential growth at the currently perceived rate throughout the forecast horizon. For forecasts of consumption over shorter horizons such as 1980 and 1985 the assumption of uniform exponential growth is clearly more likely to be valid than for forecasts over an additional 15 years. Two interpretations can be offered. First, it may be that the forecasters, through complex reasoning and application of economic theory, recognized that continued exponential growth at historical rates was unlikely over such an extended time frame and adjusted the assumed growth rate downward, particularly in the later years. An alternative interpretation in terms of behavioral decision theory would suggest a conservative bias introduced as exponential growth carries energy consumption progressively farther from its current level.

Conservatisms in judgement and forecasting, particularly in forecasting exponential growth, are well known and amply documented elsewhere (see Armstrong 1985, Hogarth 1980, Edwards 1968, Phillips and Edwards 1966, Wagenaar and Timmers 1979, Tversky and Kahneman 1974).

To correct for the obvious bias in the simulated year 2000 forecasts, equation 12 was modified to assume a linear rather than exponential extrapolation of current energy consumption growth:

$$FC(FY)_t = PPC_t * (1 + TREND_t * TPPC) * [1 + TREND_t * (FY - t)]. \quad (12')$$

The linear extrapolation does not necessarily mean forecasters believe energy growth to be a linear process. A more likely interpretation is simply that they expect the fractional rate of growth of consumption to decline in the future, resulting in a roughly linear path. The optimal parameters for the revised model are also presented in exhibit 4. The linear model generates parameters which are similar to those for the shorter forecast horizons. The MAE is 19.9 quads, an increase over the MAD

of 3 percent of the mean forecast. Exhibit 9 shows the revised model virtually eliminates the bias and captures the decline in the forecasts quite well.

Are forecasters also conservative for the nearer horizons of 1980 and 1985? The answer seems to be no: estimating the linear model for 1980 and 1985 yields MAEs of 9.1 and 8.0 quads, respectively, substantially higher than the MAEs of the exponential model for these horizons. While the estimated parameters of the linear model are not unreasonable,⁸ the linear projections underestimate the actual forecasts much more than the exponential model, suggesting the conservatism appears only for the more distant forecast horizons.

Sensitivity of the MAE to parameter variations

Consider the 1980 and 1985 exponential forecasts and the 2000 linear forecast. The estimated parameters are all between one and four years. The estimated values do not seem unreasonable given the transient response of the TREND function (exhibit 3) and the delays in measuring, analyzing, and reporting energy consumption data and forecasts. Examination of the optimal parameters shows no consistent pattern across forecast horizons for any of the parameters. But how precise are the parameter estimates? Equivalently, how sensitive is the MAE to variations in the values of the parameters? Inspection of the actual forecasts shows there is a large variance among forecasts made in a given year as well as across years. Intuition suggests the dispersion of forecasts within individual years will reduce the precision with which the parameters can be estimated.

In fact the MAE is quite insensitive to rather large variations in the parameters. Exhibit 10 shows the MAE as a function of variations in each parameter around its estimated value (holding the other parameters

constant). The error is increased only slightly as each parameter ranges from one-tenth to twice its estimated value. For example, doubling the estimated value of TPPC for 1980 would increase the MAE by about 5 percent. Only for the 1985 forecasts does the error rise substantially as the parameters vary. This is not surprising since the 1985 forecasts have a smaller within-year variance than the 1980 or 2000 forecasts. The error analysis shows that the hypersurface formed by the function $MAE(TPT, TPPC, THRC)$ is rather like a bowl with a very flat bottom--variations in the parameters produce little change in the MAE over a wide range.

The insensitivity of the MAE to variations in the parameters indicates that the differences in optimal parameters across forecast horizons are not significant. The insignificance does not arise because the model fails to explain the historical forecasts. On the contrary, the model explains the forecasts nearly as well as the median of the forecasts for each year. But the large spread among forecasts made in each year precludes strong inferences about the relative magnitudes of the parameters for different forecast horizons.

Interpreting the Results

The results demonstrate that univariate trend extrapolation of past growth in energy consumption can explain the history of energy demand forecasts for three distinct forecast horizons. The estimated parameters are consistent with known lags in the reporting of data and reasonable delays in changing perceptions of energy growth rates. The results show that adaptive trend estimation is an adequate model of the actual forecasting process, at least for such long-term forecasts as used here.

Do the results imply that energy demand forecasts are actually made by trend extrapolation or only that they can be mimicked by trend extrapolation? As noted above, forecasts of energy consumption have been made with a wide range of techniques and models. Many of these models are quite complex and are plainly not univariate trend extrapolations. Yet, regardless of the level of sophistication, each model relies upon exogenous variables or parameters, and for some of these there will be no strong theory to guide the forecaster in estimating their future values. To illustrate, the univariate model used here could be improved by using a model that determines energy consumption in terms of more fundamental economic forces. Two such models are:

$$\ln(\text{CONS}_t) = \ln(\text{EGR}_t) + \ln(\text{GNP}_t) \quad (17)$$

$$\ln(\text{CONS}_t) = a_1 + a_2 \ln(\text{GNP}_t) + a_3 \ln(P_t) \quad (18)$$

where

CONS = energy consumption (quads/year),
 EGR = energy/GNP ratio (quads/\$),
 GNP = real GNP (\$/year),
 P = average real energy price (\$/BTU),
 a_1, a_2, a_3 = regression coefficients.

The model in (17) posits energy demand as a function of GNP and the energy/GNP ratio. The model in (18) allows the energy/GNP ratio to vary with energy prices by defining energy consumption in terms of standard income and price elasticities. Such models are easily estimated and utilize more economic theory than the simple univariate trend forecast used in the simulations. But one must still forecast the values of the exogenous variables. Trend extrapolation is likely to be a dominant input to the forecasts of those exogenous variables. Elaborating the model of energy consumption does not remove the need for trend extrapolation at some level. Indeed, many of the studies whose forecasts are reported in exhibit 1 relied on large, complex, and costly models. Yet, in all these models

there are exogenous variables which must be forecast. Whether these are GNP and the energy/GNP ratio, population growth and assumed energy per capita, or population growth, assumed future technical progress, and assumed future energy prices, there is always at least one such exogenous variable for which theory provides no strong guidance. Such inputs serve as free parameters which can be used to manipulate the forecasts to be consistent with the conventional wisdom of the time. The correspondence of the simulated and actual forecasts suggests trend extrapolation acts as a strong constraint or anchor upon choice of these "free parameters".

Conclusion

The nature and rationality of expectations are hotly debated in economics and management science. Energy demand forecasts provide the opportunity for direct analysis of expectations. Despite substantial variance among the forecasts, there are substantial downward trends in the forecasts after 1973. The results show that adaptive expectations and trend extrapolation are an adequate model of the energy demand forecasting process, at least for understanding movements in the forecasts as a whole. The univariate trend extrapolation model used here provides unbiased estimates in the steady state and produces results that closely reproduce actual expectations data during a major transient adjustment period.

The analysis further suggests that for forecasts made between the late 1950s and early 1980s historic growth rates of energy consumption are extrapolated exponentially to forecast horizons of 1980 and 1985. But for forecasts made during the same period to the more distant horizon of the year 2000, the results strongly suggest a substantial conservatism. In particular, forecasters projected growth that is roughly linear rather than exponential. Detailed examination of the methodology and behind-the-scenes reasoning of the individual forecasters would be required to determine if

the conservatism resulted from explicit calculation of future energy needs, supplies, and prices or from inadvertent psychological biases.

A useful extension of the present work would be to examine the evolution of forecasting procedures at a more disaggregate level. While the model captures the evolution of the forecasts as a whole, the variance among forecasts for a given year is substantial and remains to be explained. Exhibit 1 shows that while the year 2000 forecasts of every organization drop significantly between 1972 and 1983, the relative rankings are much more stable. Energy companies and industry groups consistently produce the highest forecasts, environmentalists consistently produce the lowest. Government agencies tend to fall near the high end. This phenomenon has not gone unnoticed by the energy forecasters themselves (Lovins and Lovins 1980, DOE 1983). The stability of the rankings over time suggests that while vested interest may bias the magnitude of the forecast above or below the trend, the psychological and organizational parameters governing the process of extrapolation are common among the different groups. Such a conclusion is not surprising in view of the fact that each organization pays careful attention to the forecasts of the others. Behavioral decision theory suggests awareness of the other forecasts would tend to anchor the judgements of each forecaster to those of others (Tversky and Kahneman 1974, Hogarth 1980).

Finally, the results call into question the utility of large, complex models for forecasting purposes. Complex models may be useful, even necessary, for policy design and evaluation, for representing and reconciling alternative viewpoints or for developing theoretical understanding. But the cost and effort required to use such models for forecasting has not proven to be commensurate with their forecast accuracy when compared to far simpler and less expensive methods.

NOTES

0. The insightful comments of James Hines, Jack Homer, and George Richardson helped improve on an earlier draft. Becky Waring's technical assistance was instrumental in making the data analysis possible. All errors remain my responsibility.
1. Behavioral simulation models are a class of dynamic models which share the following characteristics:
 - (i) A descriptive rather than normative representation of human decisionmaking behavior. Decisionmaking behavior is portrayed in terms of the heuristics and routines used by the actors in the system rather than as the behavior which maximizes utility.
 - (ii) The limitations of human cognitive capacities and information processing are accounted for in modeling behavior.
 - (iii) The availability and quality of information is explicitly treated including possible bias, distortion, delay, and misinterpretation.
 - (iv) The physical and institutional structure of the system is explicit, including organizational design such as task and goal segmentation, the stock and flow networks that characterize the physical processes under study, and lags between action and response.
 - (v) A disequilibrium treatment focussing on the feedback processes which cause adjustments in the face of various external disturbances is adopted.

See e.g. Simon 1982, Cyert and March 1963, Nelson and Winter 1982, Forrester 1961, Morecroft 1983, 1985, Sterman 1985, Sterman and Richardson 1985.
2. E.g. DOE 1983 and the studies cited in exhibit 1.
3. See e.g. Mincer 1969 and Jacobs and Jones 1980. Adaptive expectations contrast against rational expectations in which expectations are assumed to be based on a true model of the system. See Muth 1961, Lucas 1976, Begg 1982. For critiques of rational expectations see Simon 1979, 1978, Klamer 1983, Shaw 1984 (especially Chapter 10).
4. The model is formulated in continuous time. It is simulated by Euler integration with a time step $dt=.125$ years, small enough so integration error is not significant.
5. The initial values of the perceived present condition and reference condition of the input are computed so that the TREND function is initialized in steady-state with respect to an assumed initial growth rate:

$$PPC_{t_o} = INPUT_{t_o} / (1 + TREND_{t_o} * TPPC)$$

$$RC_{t_o} = PPC_{t_o} / (1 + TREND_{t_o} * THRC)$$

These initial conditions avoid unwanted transients in the adjustment of TREND to the actual growth of the input.

6. The growth rate of energy consumption between 1930 and 1945 (incorporating both the Great Depression and the war) was 2.1 %/year (Schurr and Netschert 1960, p. 35). The input to the TREND function is the actual consumption of primary energy in the United States (DOE 1978 and various issues of the DOE Monthly Energy Review). The actual forecast data were acquired by digitizing the data shown in exhibit 1, using a Macintosh computer with digitizing pad. The digitizing process introduced some error, but the estimation results suggest these are of little consequence (see exhibit 10).
7. The data and hillclimbing computer program are available from the author upon request.
8. The estimated parameters for the linear model are:

	TPT	TPPC	THRC	MAE	MAE(exp. model)	MAD
1980	1.8	1.5	1.9	9.1	7.2	3.4
1985	2.1	3.0	2.8	8.0	5.7	4.1

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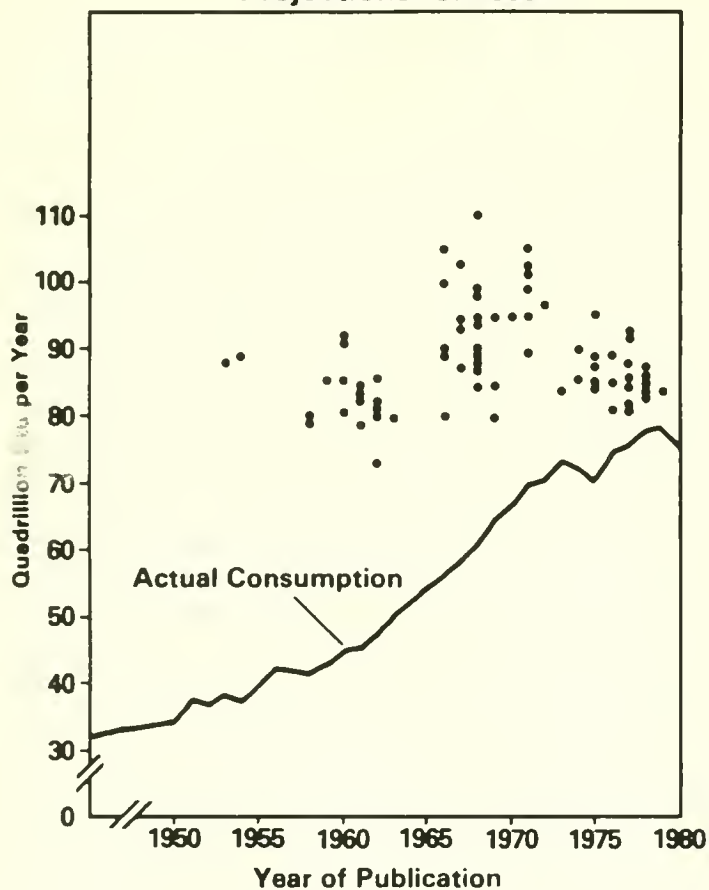
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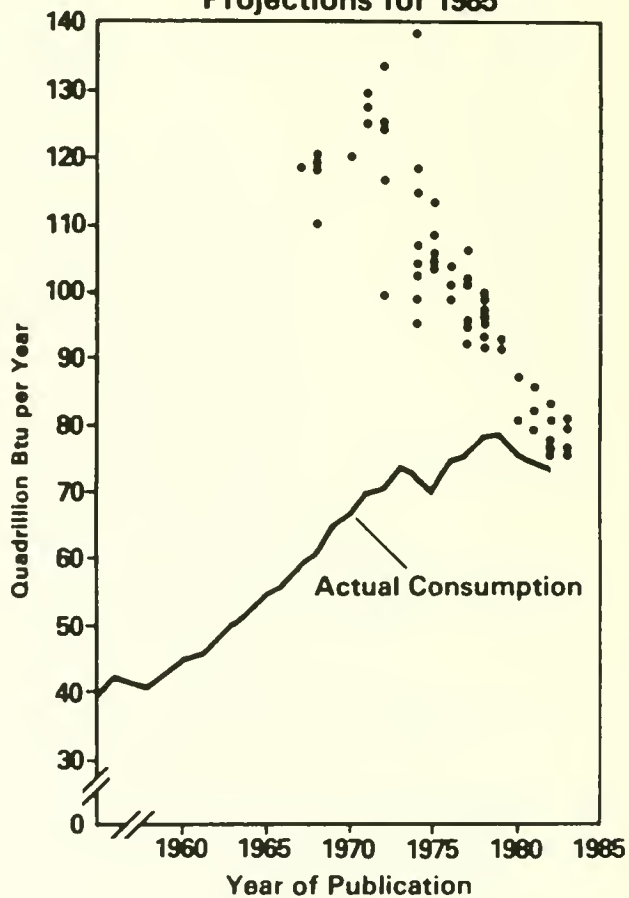
Exhibit 1a. Source: DOE 1983, p. 7-9.

PROJECTIONS FOR U.S. PRIMARY ENERGY CONSUMPTION FOR 1980 AND 1985 VERSUS REAL PRIMARY ENERGY CONSUMPTION (Quadrillion Btu per Year)

Projections for 1980



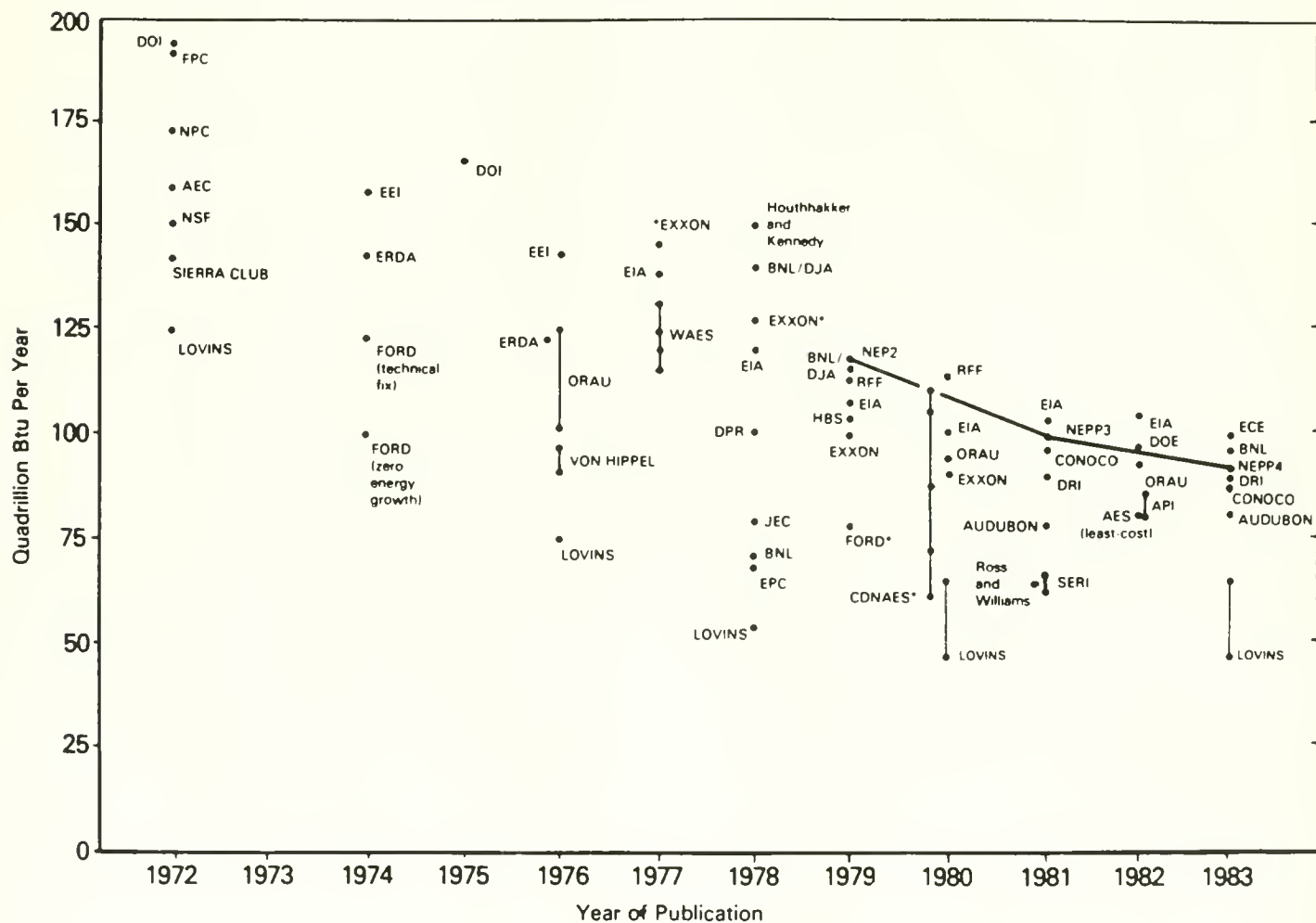
Projections for 1985



Sources. Committee on Interior and Insular Affairs (1972); National Science Foundation (1972); Joint Economic Committee (1970); Committee on Science and Astronautics (1973); Committee on Energy and Natural Resources (1978); Ascher (1978); Energy Information Administration (1977-1982); Office of Policy, Department of Energy (1979-1983)

Exhibit 1b. Source: DOE 1983, p. 7-10.

PROJECTIONS OF U.S. PRIMARY ENERGY CONSUMPTION FOR THE YEAR 2000



Sources: Oak Ridge Associated Universities(1982) and; Department of Interior(1972); National Petroleum Council(1972); Domestic Policy Review of Solar Energy, U.S. DOE(1978); Energy Information Administration(1979-1981); Office of Policy, U.S. DOE(1979-1983); Lovins(1981); American Petroleum Institute(1982); Audubon(1983); Beltramo and Manne(1983).

*Estimates derived from the study (a year 2000 number was not reported)

Exhibit 2. Causal Structure of the TREND Function

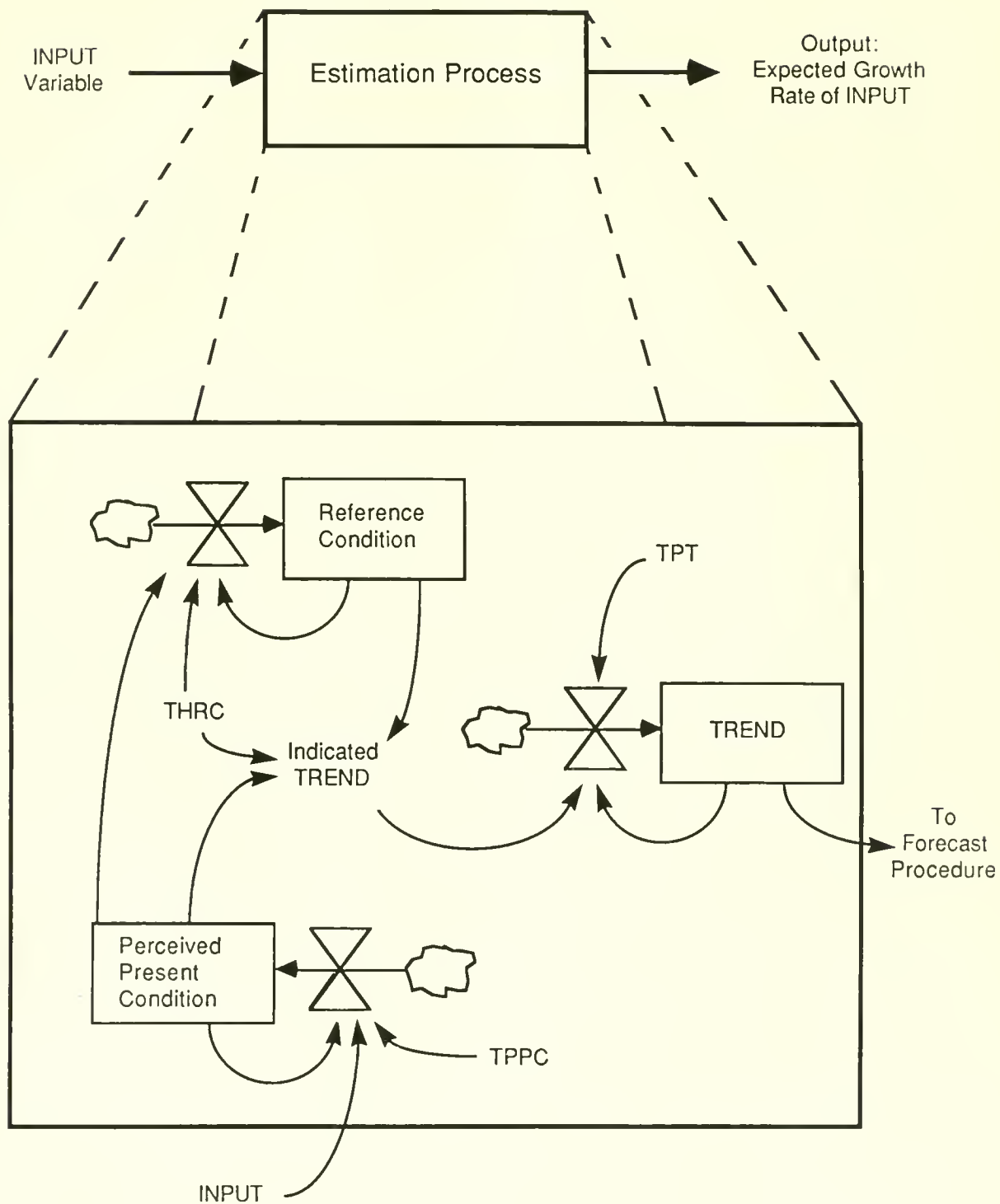
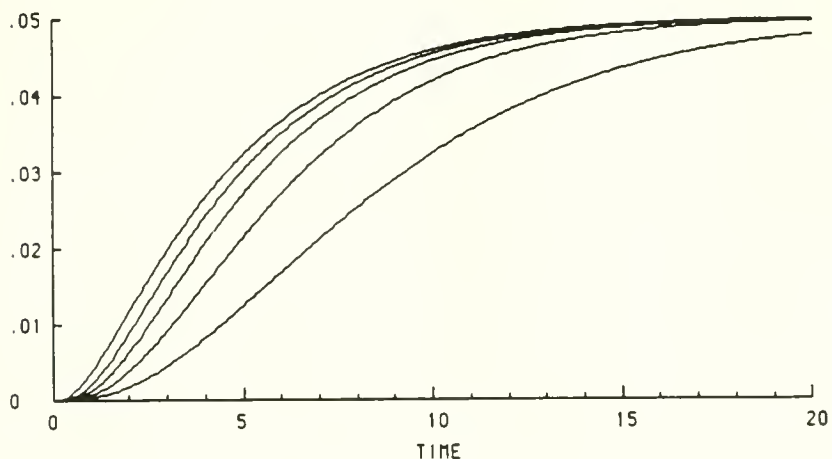
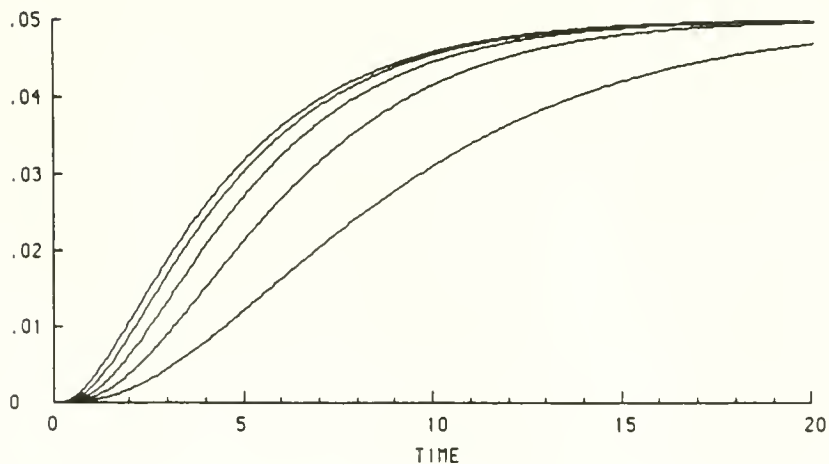


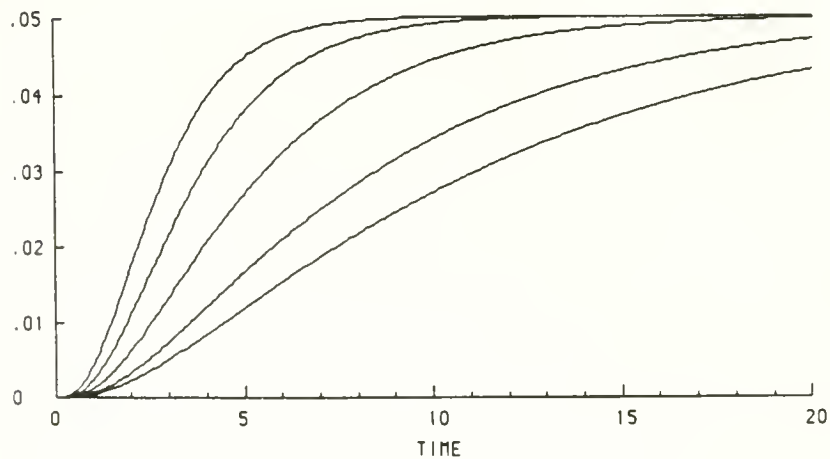
Exhibit 3: Response of TREND function to exponential growth in input of 5%/year. Shown for various values of the parameters TPPC (Time to Perceive Present Condition), THRC (Time Horizon for Reference Condition), and TPT (Time to Perceive Trend).



TPT=1, THRC=5 years.
From left to right:
TPPC=.125, .5, 1, 2, 5.



TPPC=1, THRC=5 years.
From left to right:
TPT=.125, .5, 1, 2, 5.



TPPC=1, TPT=1 year.
From left to right:
THRC=1, 2, 4, 8, 12.

Exhibit 4
Optimal parameter estimates

Forecast Horizon	TPT	TPPC (years)	THRC	MAE (Quads)	MAD ^a
1980	2.7	1.3	2.7	7.2	3.4
1985	1.2	2.4	4.0	5.7	4.1
2000 model 1 ^b	0.2	0.1	5.0	23.9	16.7
2000 model 1 ^b	1.2	2.4	4.0	33.3	16.7
2000 model 2 ^c	2.0	1.7	2.2	19.9	16.7

a MAE: Mean Absolute Error between simulated and actual forecasts.
MAD: Mean Absolute Deviation between forecasts and median forecasts for each year.

b Model 1: exponential extrapolation of expected growth rate (equation 12).

c Model 2: Linear extrapolation of expected growth rate (equation 12').

Exhibit 5: Simulated and actual forecasts of US primary energy consumption in 1980 (Quads/year)

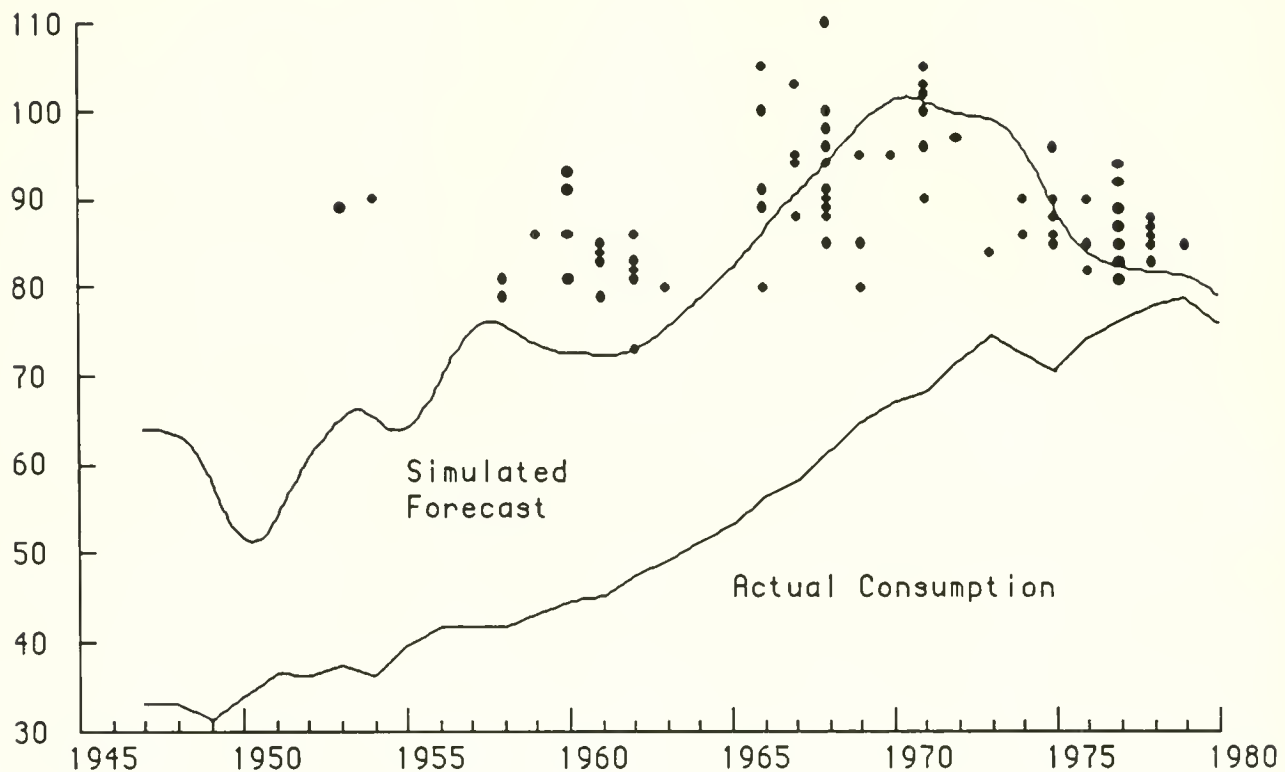


Exhibit 6: Simulated and actual forecasts of US primary energy consumption in 1985 (Quads/year)

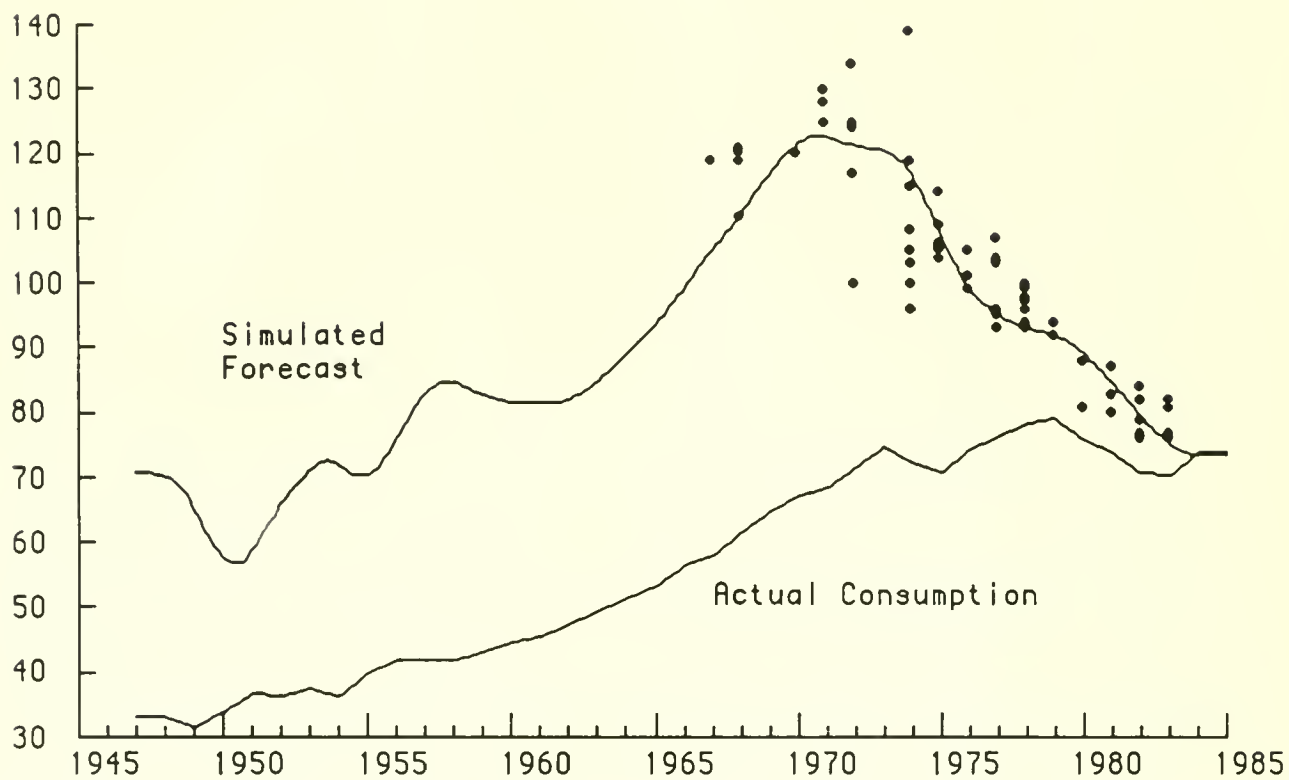


Exhibit 7: Simulated and actual forecasts of US primary energy consumption in 2000, exponential model (Quads/year)

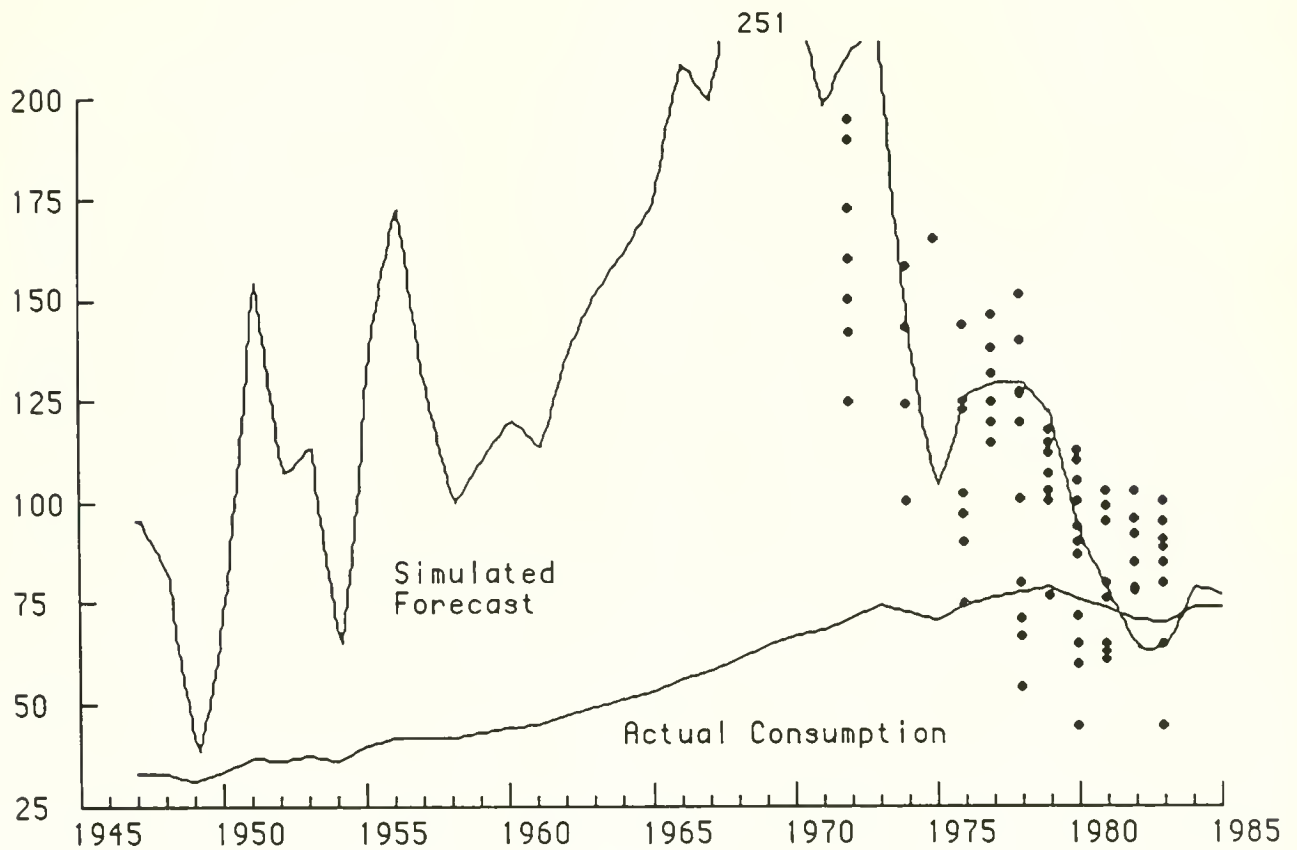


Exhibit 8: Simulated and actual forecasts of US primary energy consumption in 2000, exponential model with optimal parameters for 1985 (Quads/year)

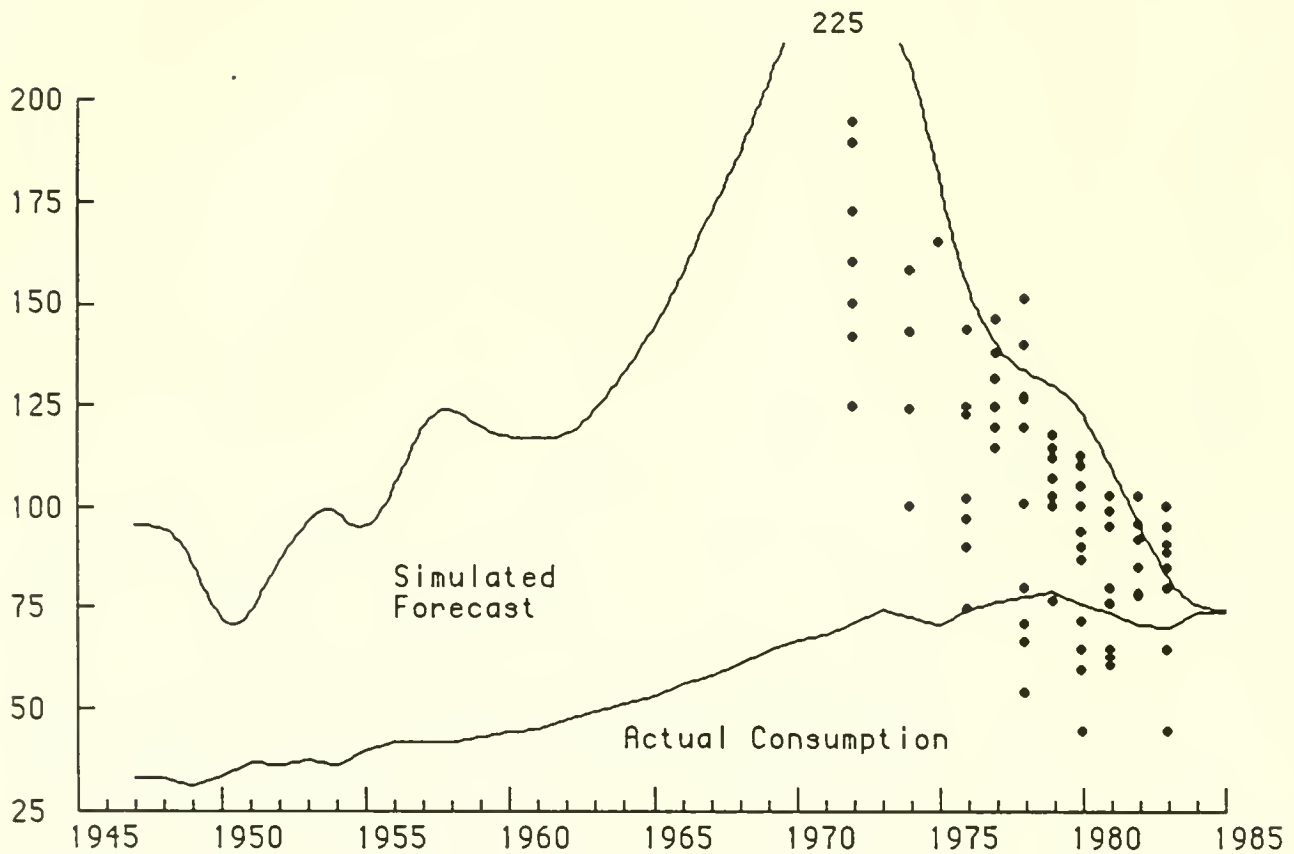
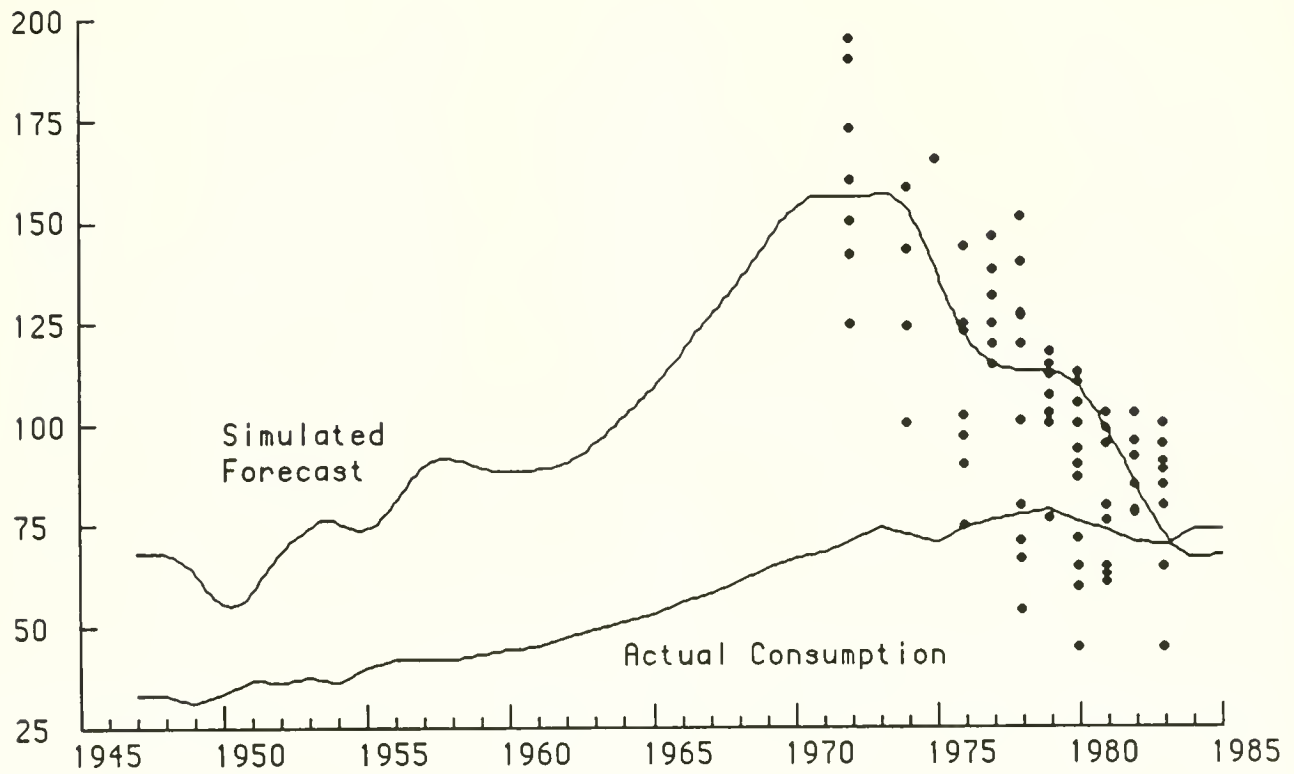
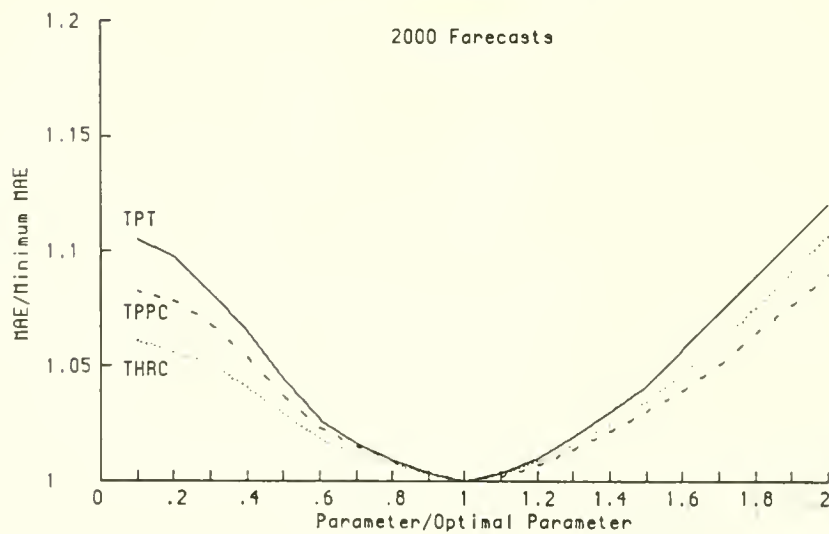
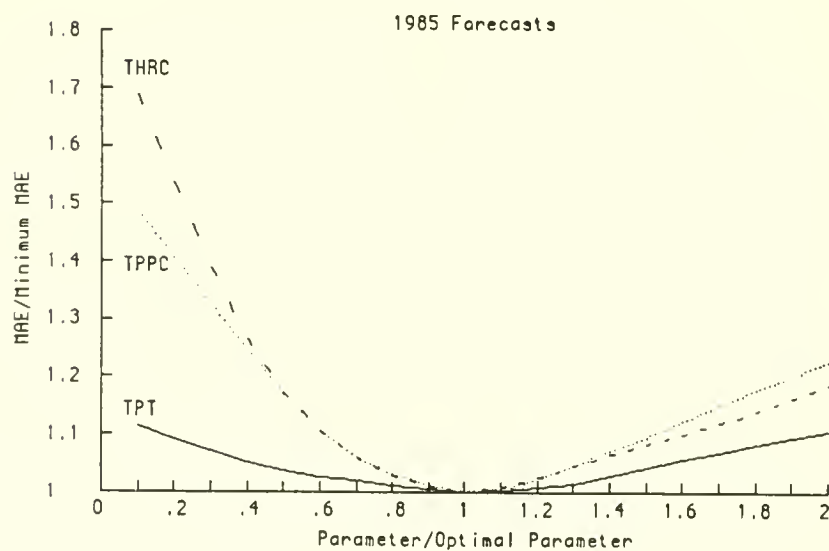
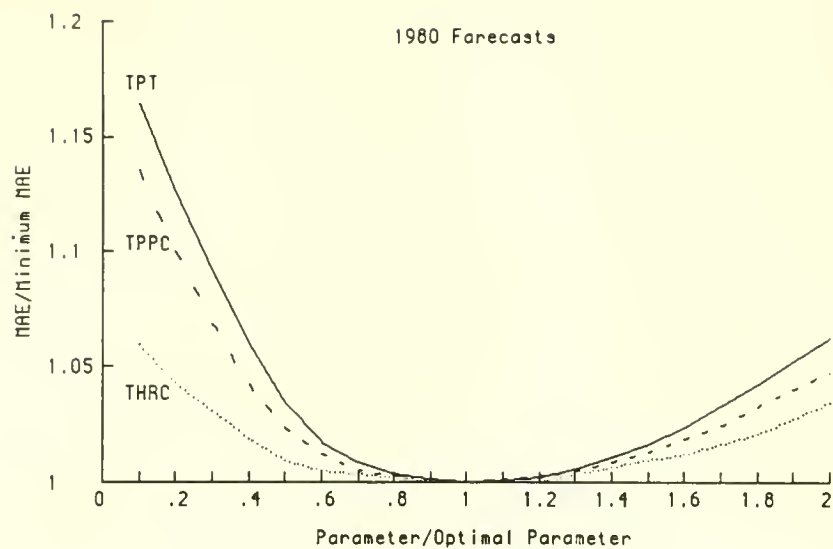


Exhibit 9: Simulated and actual forecasts of US primary energy consumption in 2000, linear extrapolation (Quads/year)





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